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Image Classification System Based on Cortical Representations and Unsupervised Neural Network Learning

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Abstract

A preprocessor based on a computational model of simple cells in the mammalian primary visual cortex is combined with a self-organising artificial neural network classifier. After learning with a sequence of input images, the output units of the system turn out to correspond to classes of input images and this correspondence follows closely human perception. In particular, groups of output units which are selective for images of human faces emerge. In this respect the output units mimic the behaviour of face selective cells that have been found in the inferior temporal cortex of primates. The system is capable of memorising image patterns, building autonomously its own internal representations, and correctly classifying new patterns without using any a priory model of the visual world.

1 Introduction

The system described in this paper was inspired by two facts which are known from neurophysiological research on the visual cortex of primates. The first fact is that the majority of neurons in the primary visual cortex react strongly, in one way or another, to oriented lines, line and curve segments, bars and edges [5, 6]. The second fact is that in certain hierarchically high areas of the visual cortex of monkeys, more precisely in the inferior temporal cortex, cells have been found which react selectively to very complex visual patterns, such as faces [3, 11]. (The availability of similar cells in the human visual system can be inferred from face recognition related deficits that can result from local neurological impairment due to lesions in the inferior temporal cortex.)

As to the first above mentioned fact, the extensive neurophysiological studies carried out in the past three and a half decades have resulted in a considerable understanding of the organisation and function of the primary visual cortex and led to computational models of primary cortical cells based on so-called receptive field functions (see e.g. [2, 4]). On the basis of such models, one can compute quantities which correspond to the activities of primary visual cortex cells when an arbitrary input image is projected on the retina, i.e. one can compute (an approximation to) the primary cortical representation of that image.

As to the second above mentioned fact, at present there is no computational model of face selective and, more generally, class selective cells. The mere fact that such cells exist is, however, an important hint for computational modeling and research, in that it is an experimental evidence that the classification of complex visual stimuli proceeds in a *convergent* way, this means, the presence of a stimulus which belongs to a given class is ultimately signaled by individual cells rather than by the collective activation of a population of remote cells.

Unfortunately, the facts known about the cortical areas between the primary cortex and the cortical areas in which face selective cells are found are not sufficient to complete the picture and become able to set up a full computational model allowing automatic classification according to and with the efficacy of the mechanisms employed by natural visual systems. In this study, a self-organising artificial neural network is used to bridge this gap in our knowledge of the visual system and to set up an artificial image classification system.

In Section 2, a computational model of simple cells in the primary visual cortex is presented and the concepts of cortical filters and images are introduced. A self-organising artificial neural network structure which consists of two consecutive layers of Kohonen networks is given in Section 3. Section 4 gives some implementation details and summarises the results.

2 Cortical filter bank preprocessor

The *receptive field* of a visual neuron is the area of the visual field within which a stimulus can influence the response of the neuron. For several classes of visual neurons, such as the retinal ganglion cells, the cells in the lateral geniculate nuclei and the simple cells in the primary visual cortex, it is possible to introduce a *receptive field function* $g(x, y)$ which can be used as an impulse response describing the response of a neuron to a small light spot as a function of position (x, y) in

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the visual field (to be denoted by Ω in the following, $(x, y) \in \Omega$). The following model is widely used (see e.g. [4]) to compute the response r of such neurons to a composite visual signal $s(x, y)$, $(x, y) \in \Omega$:

(*i*) *Linear spatial summation.*
An integral

$$\tilde{s} = \iint_{\Omega} s(x, y) g(x, y) \, dx dy \qquad (1)$$

is evaluated in the same way as if the receptive field function $g(x, y)$ were the impulse response of a linear system.

(*ii*) *Thresholding (or half-wave rectification) and non-linear contrast normalisation.*
The result $\tilde{s}$ is submitted to thresholding

$$r = 0 \quad \text{if} \quad \tilde{s} \leq T, \qquad (2)$$

where T is a threshold value (half-way rectification is a special case for $T = 0$), and non-linear local contrast normalisation:

$$r = \frac{r_\infty \tilde{s}}{c_{\frac{1}{2}} L + \tilde{s}} \quad \text{if} \quad \tilde{s} > T, \qquad (3)$$

where L is the mean illuminance within the receptive field of the concerned neuron and r_∞ and $c_{\frac{1}{2}}$ are constants which specify the saturation response and the value $(\tilde{s}_{\frac{1}{2}}/L)$ of the contrast for which half-saturation is reached, respectively (see [8] for more details of these constants in the case of retinal ganglion cells).

The classes of visual neurons mentioned above differ in the form of the receptive field function g. Retinal ganglion and lateral geniculate cells have circularly symmetric receptive fields with concentric antagonistic regions and can be described by functions of so-called Mexican hat type. In contrast, the receptive fields of simple cells in the primary visual cortex are not circular symmetric. They were found to consists of a number of oriented altering parallel excitatory and inhibitory zones, responsible for the orientation and spatial frequency tuning of these cells. J.G. Daugman [1] proposed to model the linear spatial summation properties of simple cells by complex two-dimensional Gabor functions which minimise the product of the variances in the space and spatial frequency domains. It has been demonstrated by Jones and Palmer that these functions adequately fit experimental data [7]. In the following the family of functions proposed by Daugman [2] is used in a slightly modified parametrisation:

$$g_{\xi,\eta,\sigma,\gamma,\Theta,\lambda,\varphi}(x, y) = e^{-\frac{(x'^2 + \gamma^2 y'^2)}{2\sigma^2}} \cos(2\pi \frac{x'}{\lambda} + \varphi) \qquad (4)$$

$$x' = (x - \xi)\cos\Theta - (y - \eta)\sin\Theta$$

$$y' = (x - \xi)\sin\Theta + (y - \eta)\cos\Theta$$

The arguments x and y specify the position of a light spot in the visual field and ξ, η, σ, γ, Θ, λ and φ are parameters whose effect on the function g is next explained in more detail (Fig.1).

The pair (ξ, η), which has the same domain Ω as the pair (x, y), specifies the *center of a receptive field* within the visual field. The standard deviation σ the Gaussian factor $e^{-\frac{(x'^2 + \gamma^2 y'^2)}{2\sigma^2}}$ determines the (linear) *size of the receptive field.* The response of a cell to a light spot in position (x, y) which is at a distance greater than 2σ from the center (ξ, η) of the receptive field can practically be neglected. Neurophysiological research has shown that, on the population of all simple cells, the receptive field sizes vary considerably, with the diameters of the smallest to the largest receptive fields being in a ratio of at least 1:30 [2]. The eccentricity of the Gaussian factor and herewith the eccentricity of the receptive field ellipse is determined by the parameter γ, called the *spatial aspect ratio.* It has been found to vary in a very limited range of $0.23 < \gamma < 0.92$ [7]. One constant value $\gamma = 0.5$ is used in this study.

The angle parameter Θ ($\Theta \in [0, \pi)$) specifies the *orientation* of the normal to the parallel excitatory and inhibitory stripe zones (this normal is the axis x' in eq.4). The parameter λ is the *wavelength* of the harmonic factor $\cos(2\pi \frac{x'}{\lambda} + \varphi)$. The ratio σ/λ determines the number of parallel excitatory and inhibitory zones which can be observed in a receptive field. Neurophysiological research shows that the parameters λ and σ are closely correlated; on the set of all cells, the ratio σ/λ which determines the spatial-frequency bandwidth of a cell varies in a very limited range of 0.4-0.9 which corresponds to two to five excitatory and inhibitory stripe zones in a receptive field [2]. The value $\sigma/\lambda = 0.5$ is used in this study. Typical receptive fields for the parameter values $\gamma = 0.5$ and $\sigma/\lambda = 0.5$ are shown in Fig.1a-c,e,f,h.

Finally, the parameter φ ($\varphi \in (-\pi, \pi]$), which is a phase offset in the argument of the harmonic factor $\cos(2\pi \frac{x'}{\lambda} + \varphi)$, determines the symmetry of the function g: for $\varphi = 0$ (Fig.1a-f) and $\varphi = \pi$ (this later case can be illustrated by the negatives of Fig.1a-f), the function g is symmetric, or even, with respect to the center (ξ, η) of the receptive field; for $\varphi = -\frac{1}{2}\pi$ and $\varphi = \frac{1}{2}\pi$, the function g is antisymmetric, or odd (Fig.1h), and all other cases are mixtures of these two. In our simulations, we use for φ the following values: 0 (symmetric receptive fields to which we refer as 'center-on' in analogy with retinal ganglion cell receptive fields whose central areas are excitatory), π (symmetric receptive fields to which we refer to as 'centre-off', since their central lobes are inhibitory) and $-\frac{1}{2}\pi$ and $\frac{1}{2}\pi$ (antisymmetric receptive fields with opposite polarity). As far as the phase differences of π or $-\frac{1}{2}\pi$ in this set of functions are concerned, this choice is consistent with neurophysiological data, in

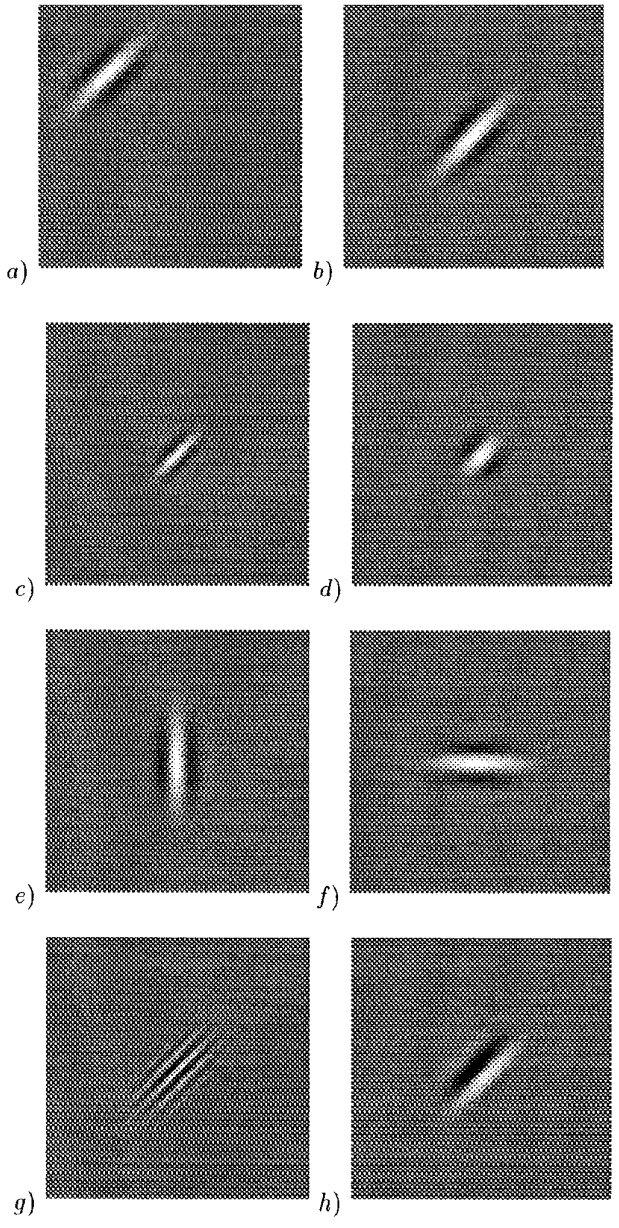


Figure 1: Receptive fields of different positions (a, b), sizes (b, c), eccentricities (b, d), orientations (e, f), number of excitatory and inhibitory zones (b, g), and symmetries (b, h). The gray level of the background labels positions in which a light spot stimulus has no effect on the firing rate of a cell. Lighter or darker colours indicate excitatory and inhibitory zones, respectively.

that adjacent cells have been found which exhibit exactly such phase differences in simultaneous recordings [14]. On the other hand, neurophysiological data shows that there are no preferred values for φ such as 0, $-\frac{1}{2}\pi$, $\frac{1}{2}\pi$ and π and that the possible values are rather uniformly spread in the interval $[0, 2\pi)$.

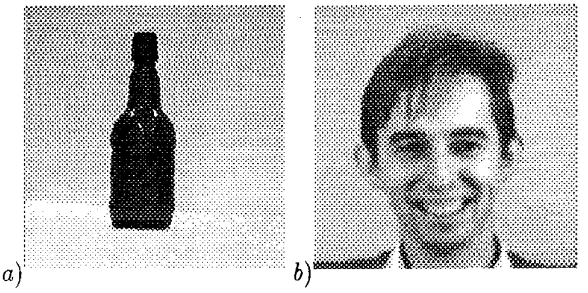


Figure 2: Two input images (size 512×512).

Substituting a receptive field function $g_{\xi,\eta,\sigma,\gamma,\Theta,\lambda,\varphi}(x, y)$ in eqs.1-3, one can compute the response $r_{\xi,\eta,\sigma,\gamma,\Theta,\lambda,\varphi}$ of a simple visual cortical cell modelled by this function to an input image $s(x, y)$. Fig.2 shows two input images for which a number of such quantities are computed and shown in Fig.3 and Fig.4, respectively, grouped together in so-called *cortical images*. The quantities grouped in one such image are computed with receptive field functions of the same values for all parameters but (ξ, η); the later specify the coordinates of a pixel to which the value of such a quantity is assigned. The filters which generate such images are referred to as *cortical filters* or *channels*. The (maximum value) superpositions of the two sets of cortical images shown in Fig.3 and Fig.4 are given in Fig.5a and Fig.5b, respectively .

Roughly speaking, the effect of such a filter is to enhance luminance transitions of a given orientation and at a give scale. The filters with antisymmetric receptive field functions are particularly selective for edges whereby those with symmetric receptive field functions are selective for bars of a given width. These selectivity properties of the cortical filters can be further enhanced by additional non-linear mechanisms in which the four filters responsible for the same orientation but having different phase (symmetry) interact with each other to produce cortical images in which either edges or bars (but not both at the same time) are enhanced in a cortical image [12].

3 Self-organising neural network classifier

Fig.6 shows a two-layer artificial neural network constructed of one-dimensional Kohonen networks [9]. In the first layer, there are m such networks, each of n nodes. Each first-layer network accepts a cortical image as input and the number m of such networks is equal to the number of cortical channels used. In this

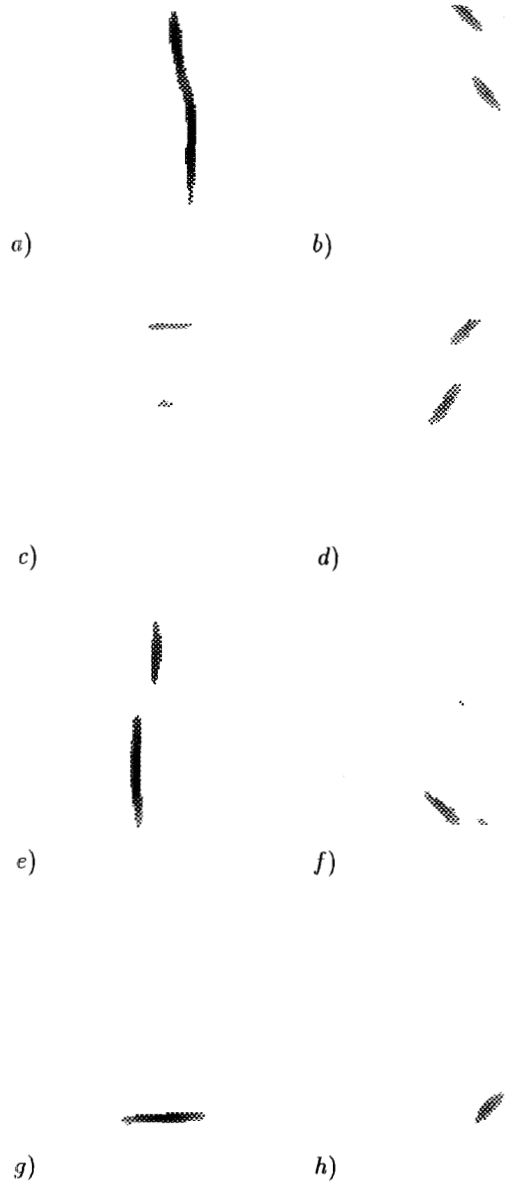
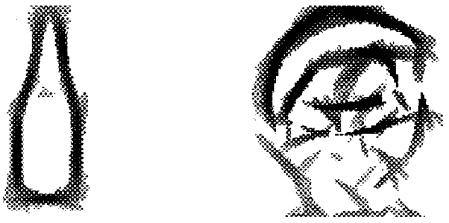


Figure 3: Cortical images computed from the input image shown in Fig.2a using antisymmetric receptive field functions of different orientations: *a)* $\Theta = 0$, $\varphi = -\frac{1}{2}\pi$, *b)* $\Theta = \frac{1}{4}\pi$, $\varphi = -\frac{1}{2}\pi$, *c)* $\Theta = \frac{2}{4}\pi$, $\varphi = -\frac{1}{2}\pi$, *d)* $\Theta = \frac{3}{4}\pi$, $\varphi = -\frac{1}{2}\pi$, *e)* $\Theta = 0$, $\varphi = \frac{1}{2}\pi$, *f)* $\Theta = \frac{1}{4}\pi$, $\varphi = \frac{1}{2}\pi$, *g)* $\Theta = \frac{2}{4}\pi$, $\varphi = \frac{1}{2}\pi$, *h)* $\Theta = \frac{3}{4}\pi$, $\varphi = \frac{1}{2}\pi$. The values of the other receptive field function parameters are: $\sigma = 32$, $\gamma = 0.5$, $\lambda = 2\sigma$. (Image size 512×512.)

Figure 4: Cortical images computed from the input image shown in Fig.2b using antisymmetric receptive field functions of different orientations: *a)* $\Theta = 0$, $\varphi = -\frac{1}{2}\pi$, *b)* $\Theta = \frac{1}{4}\pi$, $\varphi = -\frac{1}{2}\pi$, *c)* $\Theta = \frac{2}{4}\pi$, $\varphi = -\frac{1}{2}\pi$, *d)* $\Theta = \frac{3}{4}\pi$, $\varphi = -\frac{1}{2}\pi$, *e)* $\Theta = 0$, $\varphi = \frac{1}{2}\pi$, *f)* $\Theta = \frac{1}{4}\pi$, $\varphi = \frac{1}{2}\pi$, *g)* $\Theta = \frac{2}{4}\pi$, $\varphi = \frac{1}{2}\pi$, *h)* $\Theta = \frac{3}{4}\pi$, $\varphi = \frac{1}{2}\pi$. The values of the other receptive field function parameters are: $\sigma = 32$, $\gamma = 0.5$, $\lambda = 2\sigma$. (Image size 512×512.)



a) b)

Figure 5: Pixel-wise maximum value superpositions of the cortical images shown in Fig.3 and Fig.4, respectively. (The value of a given pixel is computed as the maximum of the values of the corresponding pixels of the cortical images.)

pilot study, a limited number of $m = 32$ cortical channels are used. This number results from the use of eight orientations equidistantly spread in the interval $[0, \pi)$ and four receptive field function types per orientation: two symmetric ('centre-on' and 'centre-off') and two antisymmetric functions (with opposite polarity).

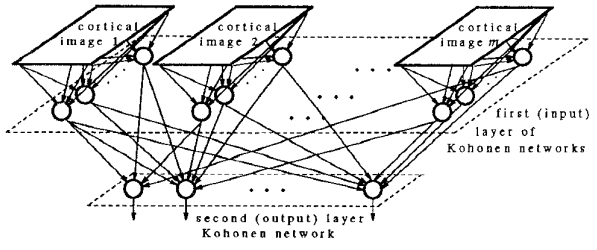


Figure 6: One one-dimensional Kohonen network is associated with each cortical filter channel, accepting a cortical image as an input. The two-dimensional activity pattern produced by the set of networks in the first layer is used as an input pattern to a second-layer (output) Kohonen network.

Since the value of σ used in this study is rather high ($\sigma = 32$), the computed 512×512 cortical images can be subsampled and reduced to a size of 32×32 to be used as input patterns to the networks.

As to the number of nodes n, it is chosen depending on the target application taking into account the following considerations: (*i*) n has to be greater than the number of classes which have to be discriminated and (*ii*) n should not be very large to prevent a very sparse assignment of units to classes and a large ensuing number of learning cycles needed to achieve convergence. In this study, the number of units used for each first-layer network is taken to be $n = 20$. This number is chosen according to the above mentioned considerations and a particular test application in which five classes of objects (images of faces, bottles, armchairs, tea cups and triangles) have to be discriminated.

For each first-layer network, the learning sequence consisted of 30 cortical images computed from 30 corresponding input images (six images per class for each of the above mentioned classes). Convergence was achieved amazingly fast — typically in less than ten epochs (presentations of the learning sequence). The fast convergence can be explained by the fact that single cortical images are very simple patterns containing a small number of features (oriented elongated connected activity regions). In most of the cases these patterns are disjunct from class to class so that, after such a pattern is assigned to a unit, it cannot be modified by patterns which arise from images of a different class. As to self-organisation, as expected the units which are activated by images of the same class tend to build clusters, but interleaved units of different classes or units which are never activated as well as mixed-class units, i.e. units which react to image patterns that belong to different classes, can also be observed.

The existence of mixed-class units means that, if one would use just one single-orientation cortical channel with one associated Kohonen network, one can get misclassifications. This is not amazing, since for complex visual input patterns, individual cortical images are not necessarily characteristic of the classes of the corresponding input images. However, *combinations of such images* are characteristic of the class to which an input image belongs as illustrated by the sets of cortical images shown in Fig.3 and Fig.4 and their respective superpositions shown in Fig.5a and Fig.5b, respectively.

The proposed two-layer network structure is based on this assumption and expected to function as follows: Each of the first-layer networks associated with the corresponding cortical channels makes its own classification of the cortical image it receives as input. One can think of the first-layer networks associated with different cortical channels as voting for different classes. These votes are counted by another network arranged in the second layer and the class which collects the largest number of votes wins.

The second-layer network has a structure which is similar to the structure of the individual networks in the first layer, in that it is also one-dimensional with the same number of units n and the same neighbourhood relations. The only difference is that, while the inputs to the first-layer networks are cortical images of size $k \times k$ ($k = 32$ in this particular case), the inputs to the second-layer network are $m \times n$ binary activity patterns produced by the m first-layer networks, each of n units ($n = 20$, $m = 32$ in this case).

The learning process for the second layer is started after the learning in the first layer is completed. The learning sequence for the second-layer network consisted of 30 activity patterns induced in the first-layer networks for the corresponding 30 input images. Similar to the convergence behaviour of the first-layer networks, the learning process for the second layer took

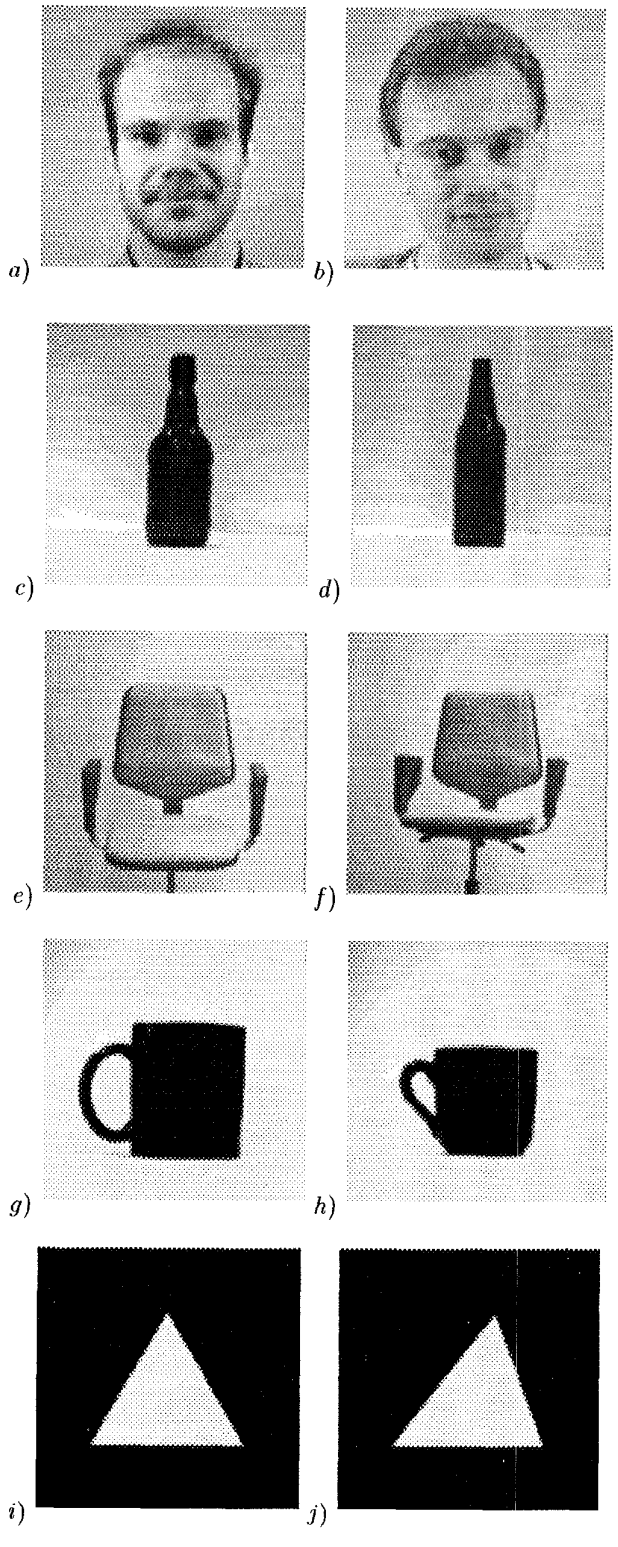


Figure 7: Representatives of the image classes used for training.

not more than ten epochs. The classification of the learned input patterns was always correct, i.e., images from different classes always activated different units. As to test patterns, until now the system was tested only for the classification of images taken under similar conditions as the learning images (compare the two columns of images in Fig.7). The system succeeded to classify all test images correctly.

An interesting question which may arise at this point is the one of how essential the cortical filter bank preprocessor is for the quality of classification. An alternative system may, for instance, use directly the input image as input data to the self-organising neural network classifier — the input image can, for instance, be split into m blocks and one such block, in place of a cortical image, can be input into a corresponding first-layer neural network. Such an experiment was carried out and it turned out that output units evolved which were activated by images of different classes, e.g. faces and chairs and bottles and cups. No mixed-class output units evolve when cortical images are used.

This result may be related to the fact that the units of a Kohonen network store patterns against which input patterns are matched. Such a matching in the input image space turns out not to be very effective: a pixel of the body of a chair may, for instance, find a very good match in a face image, since only pixel intensities are compared. Preprocessing which enhances form attributes such as edges implies matching of features which are more relevant with respect to the classification of images according to their form. As to the proposed use of a set of oriented edge detectors such as the cortical filters given above vs. an isotropic edge detector such as a Laplacian, note that the former choice prevents from matching of pixels of edges of different orientations. In this approach it is, for instance, impossible to match a pixel of a vertical edge in an input image with a pixel from a horizontal edge in a prestored image.

A statistical analysis of the likelihood of input images vs. the likelihood of their respective cortical representations with respect to form-based classification may deliver more solid arguments in support of the use of the cortical filter bank preprocessor than the qualitative explanations given above. The use of such a preprocessor in this study is based on the belief that doing things like biological vision systems do them is the right way to go, since natural selection has given rise to optimal solutions to vision problems in the given environment.

4 Summary of results, outlook, implementation and conclusions

It was demonstrated how biologically motivated models can help set up artificial vision systems which exhibit abilities that resemble the perceptual and cognitive abilities of natural systems. A most remarkable feature of the presented system is that it does not incorporate any knowledge about the visual patterns which have to be learned and classified. No model knowledge of the visual world, such as the fact that a face has two eyes, a nose, a mouth, etc., is used. The

system computes its own internal representations of visual patterns, memorises and uses them to classify new patterns. It is notable that the output units of the classifier subsystem correspond to classes of visual patterns and not just to individual patterns (generalisation property). This in a way corresponds to the neurophysiological observation that face selective cells are broadly tuned, in that such a cell would react to different faces instead of just one individual face.

On the basis of this approach, a system can be set up for which it is sufficient to put an object in front of a camera and let the system (by a key stroke) to memorise it; this action would initiate grabbing a few images of the object, possibly from different views, computing the corresponding sets of cortical representations and using them as learning input for the self-organising classifier. In a classification task, when the same or a similar object is put in front of the camera and the system is requested (by another key stroke) to classify it, the system would grab one or a few images, compute the corresponding sets of simple cell responses and use them as input for the classifier to assign a class membership to the object.

The computation of a set of cortical images for each input image is a rather computationally intensive task. This computational intensiveness is due to the convolutions (one for each cortical image) and selection operations (for the subsequent non-liner mechanisms of cortical image interaction) which have to be carried out. (Substituting a function $g_{\xi,\eta,\sigma,\gamma,\Theta,\lambda,\varphi}(x,y)$ in eq.1 and taking into account that $g_{\xi,\eta,\sigma,\gamma,\Theta,\lambda,\varphi}(x,y)$ depends on x and y via the differences $x-\xi$ and $y-\eta$ (eq.4), the integral on the right-hand side of eq.1 takes the form of a convolution. In this study, FFT and inverse FFT were used for convolution computations. The Fourier image of the receptive field function $g_{\xi,\eta,\sigma,\gamma,\Theta,\lambda,\varphi}(x,y)$ was generated directly in the frequency domain where it takes the form of a Gaussian function.)

Computing one cortical image on a powerful contemporary workstation takes approximately 5 seconds. In the current study only 32 cortical images are computed for each input image. In an ongoing extension, for each input image a set of 320 cortical images is computed (16 orientations Θ, four symmetries φ and five receptive field sizes σ) which takes more than half an hour on a powerful workstation.

In order to accelerate computations, the cortical filter bank has been implemented on a Connection Machine CM-5 scale 3 parallel supercomputer (16 nodes, 64 vector units, 2 Gflop/s, 512 Mbyte) and effective acceleration by a factor of nearly forty was achieved. Since the filter bank consists of a large number of parallel channels and there is a high degree of parallelism in each channel, we are confident that on a more powerful parallel computer the cortical filter bank can be realised to give a delay of less than a second per input image which would be comparable with the response times of natural visual systems. (First runtime measurements on a Cray J916 parallel supercomputer (16 processing nodes, 3.2 Gflop/s, 2 Gbyte) have given very encouraging results.)

The computational effort connected with the neural network part of the system depends on the number of units used. The total number of units is proportional to the product of the number of cortical filters used and the number of classes which have to be distinguished. In our first experiments, both of these numbers were relatively small (32 cortical channels and 5 image classes), so that computing time did not present a major problem both for learning and classification. The real time learning and classification for a large number of cortical channels, e.g. 320, and thousands of different image classes exceed the power of the currently available parallel supercomputers.

As demonstrated by the above example, studying and simulating the principles and mechanisms employed by natural vision systems can lead to new image analysis and object recognition techniques which may have the potential to outperform traditional machine vision approaches. Our further research will focus on studying and applying the mechanisms used by natural vision systems to extract information from cortical representations. Another topic will be the extension of the above presented simple cell primary cortex representations with representations which correspond to the responses of so-called complex cells and grating cells which do not abide to the simple cell model [10]. For further details and discussion the reader is referred to [12, 13].

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